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Radar ESM Track to Track Association

Kaouthar Benameur

Defence R&D Canada

TECHNICAL REPORT
DREO TR 2001-115
December 2001

National Defence Défense nationale

Canada

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Radar ESM Track to Track Association

Kaouthar Benameur
Surface Radar Section

Defence Research Establishment Ottawa

Technical Report

DREO TR 2001-115

December 2001

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Abstract

In this report, we present different approaches for the association of tracks for airborne sensors. The proposed approaches explore the effects of the choice of coordinate systems on the tracking filters and the association process. The performance of the association techniques is analyzed in terms of the probability of correct association (P_c) and the probability of false association (P_{fa}). This practical aspect of the multi-target multi-sensor tracking problem is presented for the association of radar tracks to ESM tracks in different scenarios.

Résumé

Dans ce rapport, on présente différentes techniques d'association de pistes générées par les capteurs d'un système aéroporté. Ces techniques tiennent compte du choix de systèmes de coordonnées des filtres de pistage, ainsi que du système de coordonnées utilisé lors de l'association des pistes. La performance de ces techniques d'association est analysée en fonction de la probabilité d'une correcte association (P_c) et de la probabilité d'une fausse association (P_{fa}). Cet aspect pratique du problème de pistage multi-cibles multi-capteurs est présenté dans le cas d'association de pistes générées par un capteur ESM à un ou plusieurs pistes radar.

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Executive summary

Using dissimilar information from both the radar and ESM (or IR) systems, different tracking and association techniques have been presented in the literature [2, 4, 5, 8, 9, 12, 16, 17]. In this report and based on a classical association technique, we present five new association approaches. We examine the performance of these association methods in relation to the choice of coordinate frames for various scenarios. The performance of these association approaches is analysed in terms of the probability of correct association (P_c) and the probability of false association (P_{fa}). This practical aspect of the multi-target multi-sensor tracking problem is presented for the association of radar tracks to ESM tracks for different scenarios.

Simulations results show that the choice of the coordinate system is a complex issue, which depends not only on the sensors but also on the scenario. One important outcome of this study is that association methods, which use bearing estimates to compute the track-to-track association, are capable of correctly associating two closely spaced targets, while association methods, which rely on measured ESM bearing for the association between tracks, are not reliable. The study also demonstrates that association method, using the polar coordinates (PC) based estimates; and the association method, using the modified polar coordinate (MPC) based estimates, have comparable performances.

Benameur K. 2001. "Radar ESM track to track association". DREO TR 2001-115. Defence Research Establishment Ottawa.

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Sommaire

Dans ce rapport, on considère deux capteurs à bord d'un avion de surveillance, on réfère dorénavant à ce système par observeur. Ces capteurs accomplissent des missions de surveillance d'un espace ou plusieurs cibles sont présentes. Le premier capteur est un radar qui mesure la distance et l'angle alors que le second capteur est un ESM (ou IR) capable de mesurer seulement l'angle.

Dans la literature [2, 4, 5, 8, 9, 12, 16, 17] , on trouve plusieurs techniques d'association de données provenant de capteurs dissimilaires. En se basant sur une technique d'association classique, on a développé dans ce rapport cinq règles d'association. La performance de ces règles est examinée en fonction de la probabilité d'une correcte association (P_c) et la probabilité d'une fausse association (P_{fa}). Cet aspect pratique du problème de pistage multi-cibles multi-capteurs est présenté dans le cas d'association de pistes générées par un capteur ESM à un ou plusieurs pistes radar dans plusieurs scenarios.

Les résultats de simulations montrent la complexité du choix d'un système de coordonnées adéquat. Ce choix dépend non seulement des capteurs mais aussi du scénario. Un résultat important de cette étude montre que les règles d'association qui utilisent les estimées d'angle pour l'association des pistes sont capables d'associer les pistes de cibles très proches alors que les règles d'association se basant plutôt sur les mesures ne sont pas fiables.

Cette étude a aussi montré que les règles d'association se basant respectivement, sur un système de coordonnées polaires et sur un système de coordonnées polaires modifiées présentent des performances comparables.

Benameur, K. 2001. "Radar ESM track to track association". DREO TR 2001-115. Centre de recherches pour la défense Ottawa.

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1. Introduction

1.1 Introduction

Design of current tactical air defence systems rely on inputs from a network of distributed sensors and/or platforms to construct an air picture and to coordinate vital mission activities such as surveillance, early warning, and weapons control. Integration or fusion of various data channels enhances effectiveness of surveillance, improves immunity to interference and deception, increases information capacity, and reduces blind zones. Current system architectures, however, consist of separate track files being maintained by individual sensors. This track data must be associated and fused to provide a coordinated assessment of the tactical environment. To address the problem of making better use of existing systems, we propose fusing the information provided by these track files. The problem of surveillance track files integration can be divided into two subdivisions: (1) on-site integration which include collocated radar integration and integration of data from dissimilar sensors (e.g., radar, ESM, IFF, etc.), (2) multi-site integration. We assume that the mission involves the detection, localization, tracking and identification of air targets using a suite of sensors. This report addresses the analysis and evaluation of data fusion algorithms appropriate for target kinematics (i.e. position, speed, etc.) obtained from radar and ESM sensors collocated on one platform.

Traditionally, the ESM sensor has produced coarse direction estimates together with increasingly reliable identity statements and this combination of data qualities poses particular problems for the fusion process. The identity statements are of increasingly high value but, in crowded scenarios, cannot currently be unambiguously associated to its target source with an associator reasoning only on ESM positional information. When fusing radar and ESM data, the higher resolution of the radar will be combined with the signature information from the ESM to contribute to an estimation of target identity. In this perspective, it is necessary to develop knowledge of data fusion techniques and to build multi-sensor tracking algorithms specific to the needs dictated by air defence systems. In this report, we develop a multi-sensor tracking algorithm that fuses information from the ESM receiver and a surveillance radar.

1.2 Background

Most currently fielded surveillance systems employ ad hoc methods for correlating tracks from multiple sources. These methods are dependent upon specific system configurations and often lack rigorous theoretical foun-

dations. Typically, little is done to fuse targets which originate from the same target. Rather, a preferred source of track data is usually identified, and the tracks from that source are used to represent the correlated aggregates, while the rest of the track file is ignored. This study pursues the development of algorithms which can integrate all available track information into composite tracks of greater quality than the constituent parts. The principle thrust of this report is the analysis of some track-to-track association techniques in relation to the choice of coordinate frames for various scenarios.

In a surveillance system, targets are detected by different sensors which exploit different characteristics of the optical, infrared, and electromagnetic spectrum. After detection, report to track association is performed and a tracker is employed to create tracks.

A difficult aspect of track level fusion is the decision process whereby tracks from different sources are determined to represent the same target. In this report, kinematic track association is performed . It is assumed that all remote tracks are transmitted to a centralized fusion center. Track fusion is performed by employing a weighted covariance algorithm. For two-sensor track fusion, this algorithm combines associated tracks by weighting each of these tracks by certain covariances which are functions of their respective filtering and variances.

The algorithms developed in this report are implemented in MATLAB. These algorithms are tested by creating Airborne Surveillance Scenarios which consist of two targets following different trajectories. These targets are sensed by two sensors (Radar, ESM) which are collocated on the same platform.

1.3 Overview

This report is organized as follows: In Section 2, we present the basic operational characteristics of the radar and ESM sensors. Section 3 summarizes the basic data association methods that have been discussed in the literature. In Section 4, we define the three different scenarios used to evaluate the effect of the selection of the coordinate system on the association process. Section 5 presents the tracking filters in different coordinate systems. In the first part of Section 6, we present the association approaches considered in this report which involve the selection of the coordinate systems for the trackers and the decision rule. Details of numerical simulation of the fusion algorithms are presented in the second part of Section 6. Finally, summary of this study and some concluding remarks are contained in Section 7.

2. Sensors

A basic understanding of sensor operational characteristics is essential to the understanding of the motivation and the design of any tracking system. Our goal in this section is to present the elements of generic models for ESM and radar sensors. For each sensor, we outline the current sensor technology in terms of tracking with just enough detail to account for the features which influence the tracking system and its performance.

In terms of tracking system, we focus on two basic classes of measurements: kinematic and attribute. Kinematic measurements provide the tracking system with information about the relative position of the target with respect to the sensor. Typical kinematic measurements for radar and ESM sensors include relative range, bearing, and elevation angles. As with kinematic measurements, attribute measurements also provide the tracking system with information about the existence of one target or more. Attribute measurements are harder to universally qualify or quantify than kinematic measurements. Typical attribute measurements might include:

- Signal features extracted from intercepted signal,
- Coarse kinematic information such as maximum observed speed, which may also serve as an ID distinguishing attribute.

2.1 Radar Sensors

There are many types of radars that vary depending on the function radar is intended. Grouped according to their functional classification these types are:

1. surveillance radar,
2. fire control radar,
3. radar for navigation, and
4. mapping radar.

In this section, we restrict our attention to target acquisition and tracking radar modes as opposed to mapping.

Radar has to detect and evaluate the position of targets inside a specific area of coverage and to maintain a re-evaluation of this area periodically and automatically. To perform this task a surveillance radar has to detect and track targets and discriminate the targets of interest among the clutters. A fire control radar has to

guide a weapon such as a missile to the target the radar is locked on. A navigation radar is used to control the trajectory of a moving platform carrying the radar.

The fundamental characteristics of surveillance radars are the wavelength and the automatic tracking modes [7]. The electromagnetic wavelength of the radar transmitter beam is of the order of 5cm for a typical medium range radar and 30cm for a typical long range radar. In general, range and azimuth resolution could be used to provide clues about target identity but for surveillance radar this is technically impossible due to the used beam wavelength which is large to permit high range and cross-range resolution. Also, most of the surveillance radars use track-while-scan approach to perform the automatic tracking task.

During basic search operation, modern tracking radars are capable of measuring target angle (azimuth and elevation), range, and range rate. The radar scans its antenna while transmitting and subsequently receiving pulses of energy. It processes the energy reflected from objects to detect their presence and various kinematic quantities.

The radar transmits a pulse of RF energy with pulse width τ. This pulse travels out to the target, is reflected by the target, and returns to the radar t seconds later. The radar's receiver detects the presence of the returning pulse and measures the round-trip travel time t and hence the range. A practical radar design checks for a returning pulse at a number of discrete ranges (range bins) by matched filtering of the returning pulse against a set of discrete delayed versions of the transmitted pulse.

The radar measures angle by noting the azimuth and elevation angles at which the aperture is pointed during the time the returning pulse is detected. The azimuth and elevation along with the measured range provide the 3D relative position of the target with respect to the radar. Modern Doppler radars have the ability to measure the range rate of a target by coherently integrating many pulses of returning energy against the known transmitted signal and hence measuring the Doppler shift that the target causes. Generally, the radar assesses Doppler shift by collecting one complex sample (one sample from the I and Q channels of the receiver) from each of N consecutively received pulses or equivalently for a fixed time called the coherent integration time. In phase and quadrature (I /Q) processing can be thought of as forming two matched filters 90° out of phase. Thus the returning pulse (which is of unknown phase) is projected onto the two orthogonal I/Q axes in signal space. The signal's two coordinates in signal space are referred to as a complex sample. The radar then uses N consecutive samples to form the complex FFT. The sampling rate is the Pulse Repetition Frequency (PRF). Consequently, the Doppler will alias at the complex Nyquist rate equal to the sampling frequency. Therefore, in the frequency

domain, there is a Doppler ambiguity folding analogous to the range ambiguity folding in the time domain.

2.2 Electronic Support Measure Receivers

ESM receivers function to search, intercept, locate, and identify sources of enemy electromagnetic radiation. The information they produce is used for the purpose of threat recognition and for the tactical employment of military forces or assets such as ECM equipment. The ESM function is reserved for real-time reaction which serves to differentiate between ESM receivers and ELINT or COMINT receivers [24]. The latter types are used for intelligence collection purposes, which generally involve subsequent or non-real-time analysis of the intercepted data.

ESM equipment for radar signal intercept falls into two broad classes: (1) radar warning receivers (RWR) used by aircraft, ships, and ground forces for self protection and (2) reconnaissance/surveillance receiver systems used to intercept, collect, analyze, and locate radar signals in near real-time so as to update the local electronic order of battle (EOB) for targeting, ECM deployment, early warning of enemy approach, and fusion with other sensors.

RWRs are generally the simplest form of ESM receiver consisting of an unsophisticated low-sensitivity equipment which is preset to cover the bands and characteristics of expected threats and which exploits the range advantage to indicate a threat before it reaches its firing range. ESM reconnaissance or surveillance receivers are generally more complex than RWRs, and they are used to map enemy radar and communication installations and to monitor radio messages. The more elaborate radar ESM receivers are similar in concept to RWRs, except that they generally employ more sensitive receivers to intercept radar sidelobe radiations at long ranges, have higher direction finding accuracy , and measure additional radar parameters such as coherency, polarization, pulse shape and artifacts, intrapulse modulation, and statistical features. In this report, the term ESM is taken to mean any level of electronic warfare antenna/receiver system capability, from RWR , through ESM.

The data that ESM can contribute to the fusion process are:

- Azimuth Direction of Arrival (DOA) and, in some instances Elevation DOA,
- Emitter, mode and associated platform identification, each with a recognition confidence factor,
- Time of Arrival (TOA) and range to the emitter, and
- Priority, if the emitter is a threat.

The ESM, dependent upon its capability, may also provide measured emitter RF parameters (e.g. fundamental parameters of frequency, Pulse Width and Pulse Repetition Interval, received power, and scan time/rate) and emitter location (from DOA and range). Derived parameters include RF type (fixed, hopper, deviation, etc.) and scan type (circular, conical, etc.). The accuracy of the DOA, quality of and confidence in the above identification and speed with which the ESM determines them, determine their importance to the fusion process.

ESM systems use DOA determination techniques which are based upon the measurement of some combination of amplitude, phase and time of arrival of an emitter's RF signal at a number of co-located and/or remotely located receive antennas. The resulting DOA accuracy is primarily a function of antenna type and locations, combined with receiver measurement accuracy of frequency, time and phase.

Electronic "fingerprints" of emitters and emitter types are discussed in the literature [24]. Although there are differing interpretations of the term "fingerprinting", it means the use of a unique set of measurable parameters which enables either differentiation between emitter types or between emitters of the same type. Significant commonality of RF parametrics of hostile and friendly radars limits the ability of current EW systems to provide an unambiguous identification of the illuminating emitters. Another problem of ESM capability limiting its usefulness to the determination of a real-time tactical picture is the update rate of track file information. The ideal ESM performance requirement is to see only the leading edge of the RF signal and to instantly and unambiguously recognise the emitter, classify friend or foe, etc. In reality a few pulses and a few seconds are required to achieve the above with any degree of confidence.

Emitter location is not, strictly speaking, a part of the process of signal interception. Because the measurement of angle of arrival is usually one of the basic functions of the signal interception process, a by-product is obtained by using the DOA measurements to estimate the actual location of the emitter. In a similar way, the cross-correlation of signals received from separated intercept sites is a way of detecting signal energy which yields the differences in the times of arrival of the energy at the various sites. These time of arrival differences may also be used to estimate the emitter location.

Although different techniques exist for emitter location, only three are strictly applicable to military aircraft in the wingspan/length range 15 m (fighters) to 35 m (maritime patrol aircraft). These techniques are:

1. Azimuth, Elevation: Ground emitters can be located instantaneously, assuming the use of aircraft altitude and reasonable DOA accuracy, either amplitude comparison (low cost) or interferometer (high cost) direction finding techniques. The down- and cross-range errors are a function of DOA errors, height accuracy and range to emitter. The ranging accuracy of this technique is best at high altitude (large depression angles) and degrades rapidly at low altitudes (an appreciable limitation for low level operations).
2. Triangulation: The aircraft takes azimuth (or bearing) measurements at regular intervals of a few seconds, and uses triangulation and estimation algorithms to arrive at an accurate emitter location within a few seconds.
3. Time Difference of Arrival (TDOA): Traditionally this has been a multi-platform technique, but can be implemented successfully on a large aircraft, now that TOA measurement systems with 1-5 ns resolution are available. It is a complex technique and technology, yielding high accuracy with high speed (at high cost). It is unlikely to be feasible on a fighter-sized airframe due to the need for very wide spacing of antenna to form TDOA measurement baselines.

In each of the above techniques, various methods can be used to resolve location ambiguities and reduce overall emitter position error. One of the simplest methods is range estimation by the comparison of measured signal power against that stored in the ESM's emitter database.

Based on these techniques, ESM has traditionally produced coarse emitter location and an increasingly reliable identity statement. This data quality poses an association problem: the identity attributes are of increasingly high value but, in crowded scenarios, cannot currently be unambiguously associated with individual track.

3. Data Association

In a multitarget multisensor environment it is necessary to first pair the measurements with the correct sensors tracks. This procedure is known as data association that includes gating, association, track initiation, confirmation, and deletion functions.

In this report, we deal with association techniques for information provided by radar and ESM sensors. These techniques are identified by Level 1 fusion in the JDL model. The JDL Data Fusion Model, defines four levels of fusion. Figure 1 represents the JDL data fusion model as described in [8,26,17]. This data fusion model is the most widely used for classifying data fusion related functions. In Level 1, sensor(s) or source(s) reports are aligned, associated, and combined to refine the state estimate of detected objects using all available data from each object. The sequence of operations in the first level may be described as follows [17]:

1. Alignment: All observations must be aligned to common spatial and temporal frames of reference.
2. Association: Once in a common frame of reference, the observations are correlated to determine which observations are derived from the same target. Correlation metrics generally include spatial (same location), spectral (similar observed characteristics) and temporal (same time of appearance) parameters. If the correlation metric for a pair of observations is sufficiently high, the observations are assigned to a common source object.
3. State Estimation: The state of the object (the location if the object is stationary, or a dynamic track if the object is moving) is updated using all associated observations.
4. Object Identification: The identity of the object is also estimated using all available measurements. If the sensors measure diverse characteristics of the object (e.g., colour and shape) automatic classification techniques are applied to resolve the identity.

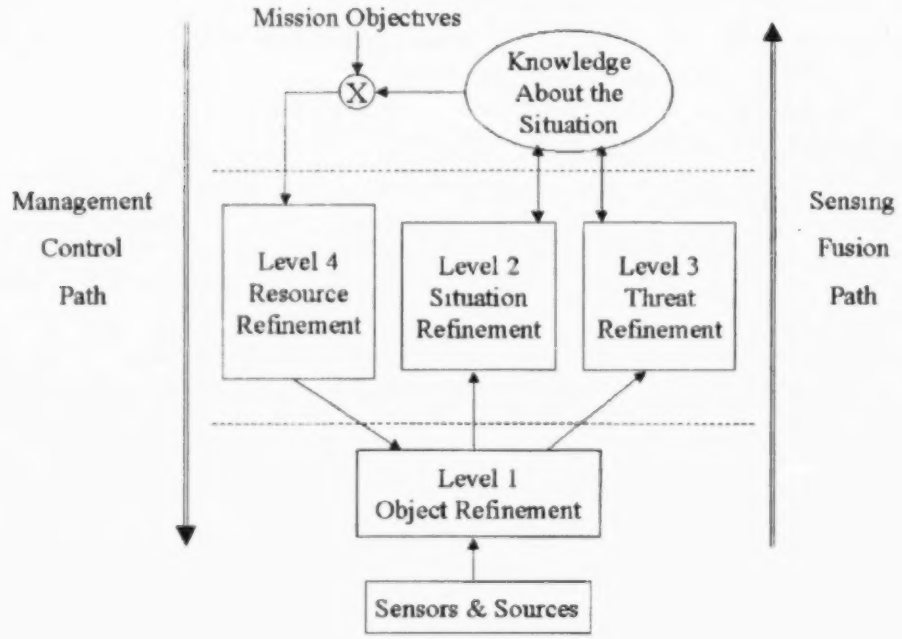

Figure 1. *JDL Data Fusion Model*

In this report, we are concerned with Level 1 of the data fusion model. The purpose of the association is to amalgamate multiple sensor observations (measurements) from

a common object (target) into a group and to develop a dynamic model of this object. In other words, this model represents a track of the target based on the sequence of measurements in the group. Once tracks are established, an observation-to-track association is performed to determine if the new observations can be associated with the existing tracks.

Data association techniques can be classified as sequential assignment techniques and multiple hypothesis (deferred logic) techniques. Deferred logic techniques attempt to solve the association problem via the optimal Bayesian method but usually opt for a maximum likelihood criterion. Unfortunately, the Bayesian solution is not amenable to implementation [16].

Sequential assignment techniques formulate the problem as a hard assignment of each observation or as virtual observation assignment. The virtual observation assignment involves the probabilistic computation of relative likelihoods [26,3]. This is accomplished in such a manner that the combined likelihood of these assignments is maximized, which is the equivalent to choosing the combined observations with the minimum distance between them.

Details of the classical, sub-optimal association algorithms are presented in the following subsection.

3.1 Classical Data Association

Most classical data association methods are based on the Nearest Neighbour (NN) approach (including single-hypothesis and multiple-hypothesis techniques) and on the All Neighbour method (including Joint Probabilistic Data Association (JPDA)). Non-algorithmic (approximation) methods including fuzzy logic, knowledge-based techniques, and neural networks have also been proposed as association approaches [4,5,23,22]. In the following, we present a brief description of some classical association techniques. A complete definition for these techniques may be found in references [3,2,5,22,23,26].

3.1.1 The Nearest Neighbour

In the NN technique, the measurement closest to the predicted estimate is used to update the target states. The Euclidean distance usually defines this measure "of closeness". Other measures of closeness can be used [3] where it is proposed to use the norm of the innovation squared to define the NN filter. When using the NN approach, a single observation can be associated for the purpose of updating, thus creating an ambiguity in data association.

While this approach works reasonably well in scenarios with few targets with reasonable signal to noise ratio, the performance of the technique degrades when:

- Signal to noise ratios are very low (i.e., the probability of detection is small).

- The false alarm rate is high.
- The target is partially observable (passive targeting) [18].

3.1.2 The Greedy Method

Another assignment method is the so-called "Greedy" method, whereby the assignments are ranked and the best available assignments are selected. This is accomplished by picking a track at random and assigning the observations from each sensor that are the closest to it. Then, a second track is selected randomly and the process is repeated. The Greedy association approach eliminates observations and tracks as they are assigned and does not allow an observation to be used more than once. Also, this method does not allow a track to be assigned more than one observation per sensor.

The Greedy method is particularly suited to the problem of observation-to-observation association for passive sensors where bearing only measurements are provided. Because no range information is available, the problem of an exponentially increasing number of ghost targets arises as the number of observations and sensors increases. In this type of scenario, the deferred logic approach becomes impractical for large number of targets (reference [17] suggests that the technique become untrackable for more than 10 targets).

3.1.3 Global Nearest Neighbour

The Global Nearest Neighbour (GNN) is the simplest and probably the most widely applied data association method. This approach provides a unique assignment so that at most one observation can be employed to update a given track. In this technique, an observation is utilised to update at most one track. Because this method handles the input data in a purely sequential manner, it is also referred to as a single hypothesis or sequential most probable hypothesis tracking technique.

This technique fails in situation where there are more than one observation or there are more than one target in a gate [26].

3.1.4 Probabilistic Data Association

The Probabilistic Data Association (PDA) was developed by Bar-Shalom and Tse [4, 11]. The PDA, also called the All-Neighbour approach, is designed to improve the performance of the GNN method, which seeks the single most likely hypothesis. In this approach, multiple hypotheses are formed every time more than one measurement is found in the validation gate (region where true measurement will appear with a high

probability [2]). The measurements are threshold and the ones, which are within the threshold, are associated with the track. The probability of each measurement in the gate is computed and the overall estimate is obtained by combining the estimates from each measurement according to its association probability. This is the reason it is called the "All Neighbours" approach.

Although assumed to be a very good method for tracking targets in dense clutter without requiring large processor and/or memory, the PDA assumes that a target track exists and it cannot be used for track formation [10] Solutions to this problem have been proposed in [21,26].

3.1.5 Joint Probabilistic Data Association

The Joint Probabilistic Data Association (JPDA) approach is an extension of the PDA method that includes multiple targets in clutter. The JPDA method is similar to the PDA with the exception that the association probabilities are evaluated using all tracks and all observations. Although the JPDA gives a better performance than the simpler data association methods and requires less computational power than the Multiple Hypotheses Tracking (MHT), it can pose problems with its implementation and require extensive computational resources in dense environment. Several modifications to the JPDA algorithm have been proposed in [2,16] to solve the computational burden of this algorithm including the Cheap JPDA, the Nearest Neighbour JPDA, and the Sub-optimal JPDA.

3.1.6 Multiple Hypothesis Tracking:

The Multiple Hypothesis Tracking (MHT) method considers the association of sequences of measurements and evaluates the probabilities of all association hypotheses formed whenever observation-to-track conflict situations arise. Then, the hypotheses are kept in anticipation that subsequent data will resolve the uncertainty, rather than combining them, as in the JPDA approach.

The problem with this technique is that it requires the evaluation of an exponentially increasing number of feasible data association hypotheses. Techniques like Depth First Search, Limited-Search MHT, Pruning, and Merging have been proposed in [2,5,12,16,17] to limit the number of hypotheses to be stored.

3.1.7 Knowledge-Based Methods

Finally, new sets of techniques are being applied to tracking, and can be broadly characterized as knowledge-based methods. These methods are neural network applications, genetic algorithms which use qualitative/heuristic information, and fuzzy logic. The basic idea behind these approaches is to complement the usual model-based statistical methods with learning and reasoning methods based on human intelligence and biological learning [16,17,22].

The data association from multiple sensors is a crucial step in the fusion process. Therefore, in this report, we consider a practical aspect of the association of ESM observations and tracks with one or more of m possible radar tracks. We examine the performance of different association techniques in relation to the choice of coordinate frames for various scenarios. We evaluate different track-to-track and observation-to-track data association algorithms depending on the scenarios and dynamics of the targets. De-centralized data association approaches using the likelihood function are evaluated and compared for different scenarios. The performance of these techniques is analysed in terms of their Probability of False Association (P_{fa}) and Probability of Correct (P_c) association.

4. Problem Formulation

4.1 General Scenario

In this report, we consider the following scenario: two sensors on board an aircraft (observer) carrying out surveillance over an area where multiple targets are assumed to be present. The first sensor is a radar providing range and bearing measurements and the second sensor is an ESM system providing bearing only measurements (Figure 2).

In the surveillance mission, tracking and identification of targets is an important task and this task is dependant on the sensory suite available to the operator and the prevailing environment. A radar, for example, provides reasonable positional accuracy of the target but has a poor identification capability. On the other hand, the ESM system provides poor positional accuracy of the target but is capable of providing precise identification of the target. Evidently, to achieve an acceptable performance in both tracking and identification areas, it is worthwhile to combine the two sensors.

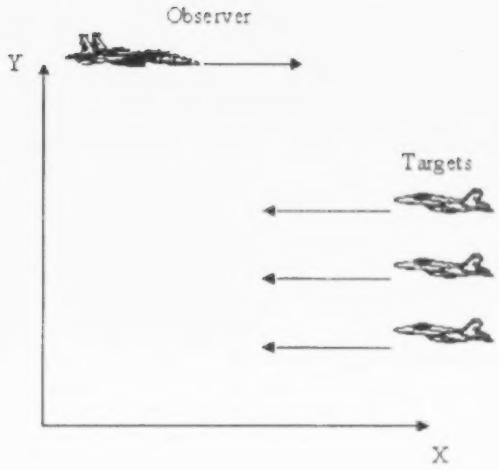

Figure 2. *General Scenario*

Using dissimilar information from both the radar and ESM systems, different association techniques have to be explored based on the kinematics information. For example, one can obtain the measured bearing from the ESM (θ_{esm}) and from the radar (θ_{radar}). At this point, we need to determine if these bearing measurements are coming from the same target. The use of multiple-sensors data fusion techniques allows us to insure correct association and tracking of the measured bearings.

When data first arrive at the track-to-track fusion process, the number of targets is still unknown. If two sensors reported two targets each, ignoring false alarms, the possibilities that there are two, three or four targets being tracked jointly by the two sensors must be considered. A data association procedure, which is linked to the likelihood of making the right decision, may be considered to account for the different possibilities.

The ability to produce an unambiguous solution to the association problem depends on the scenario. The problem of association can be easily handled when the targets are dispersed and tracks from different targets are unambiguous and/or when similar targets are grouped very tightly so that track from the same class may be interchanged without affecting the solution. However, when dissimilar targets lie close together (Figure 3), incorrect associations can be made which, in turn, can affect the quality of the fused information.

ESM data is particularly prone to the latter problems because it tends to produce tracks with the coarsest positional accuracy. However, at the same time the identity information generated by this system can be very precise and accurate. Thus, there is a great incentive to use the ESM system.

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In this report, three different scenarios are analyzed under the assumption that the ESM and radar measurements are synchronized.

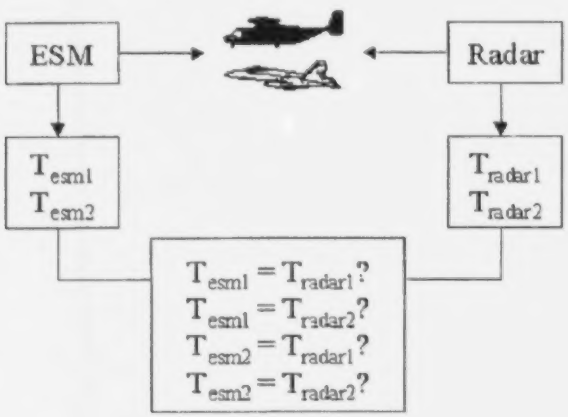

Figure 3. *Close Target Association*

4.2 Profile A

Under the assumption that the ESM and radar measurements are synchronized, Profile A represents a scenario where two targets are moving toward the observer at a constant speed and heading as shown in Figure 4 below. We assume that the observer's trajectory is known.

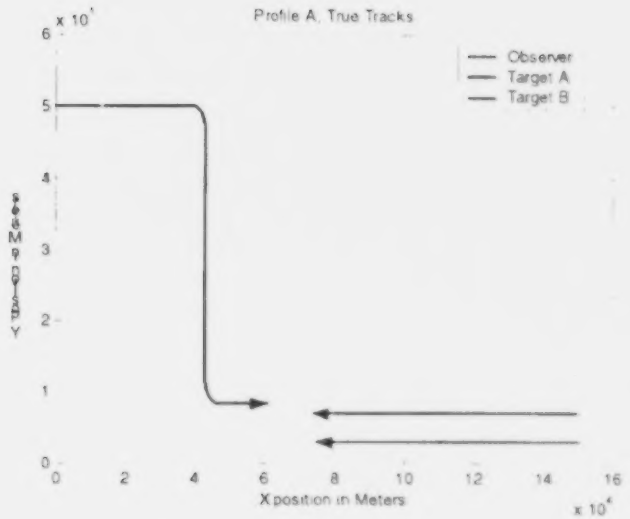

Figure 4. *True Tracks for Profile A*

The initial kinematic parameters of the observer and the two targets for Profile A, are listed in Table 1 below. The separation between targets $p = 4.000$ meters, in this case.

Table 1. *Initial kinematic parameters for profile A*

PARAMETERS	OBSERVER	TARGET A	TARGET B
X(m)	0	150,000	150,000
Y(m)	50,000	3,000	7,000
x (m/s)	200	-150	-150
y (m/s)	0	0	0

4.3 Profile B

Profile B shows a scenario where two targets are moving away from the observer at a constant velocity and heading as shown in Figure 5.

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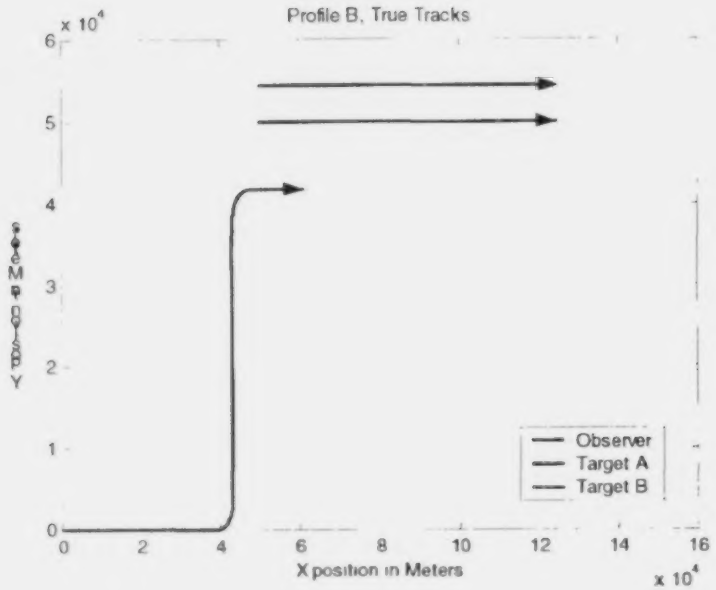

Figure 5. *True Tracks for Profile B*

The initial kinematic parameters of the observer and the two targets for Profile B are listed in Table 2.

Table 2. *Initial kinematic parameters for profile B*

PARAMETERS	OBSERVER	TARGET A	TARGET B
X(m)	0	50,000	150,000
Y(m)	0	50,000	54,000
x (m/s)	200	150	150
y (m/s)	0	0	0

4.4 Profile C

The final scenario is Profile C. In this profile, two targets are moving away from the observer at a constant speed and heading, but the targets are flying at a 45 degree angle as shown in Figure 6.

This geometry offers a good compromise between increased bearing rate and reduced relative range allowing the velocity errors to be minimized. This, in turn, will benefit the ESM filters as the bearing rate is increased when the observer crosses the target's Line Of Sight (LOS), which results in a substantially improved estimation of the bearing [25]. The initial kinematic parameters of the observer and the two targets for Profile C are listed in Table 3.

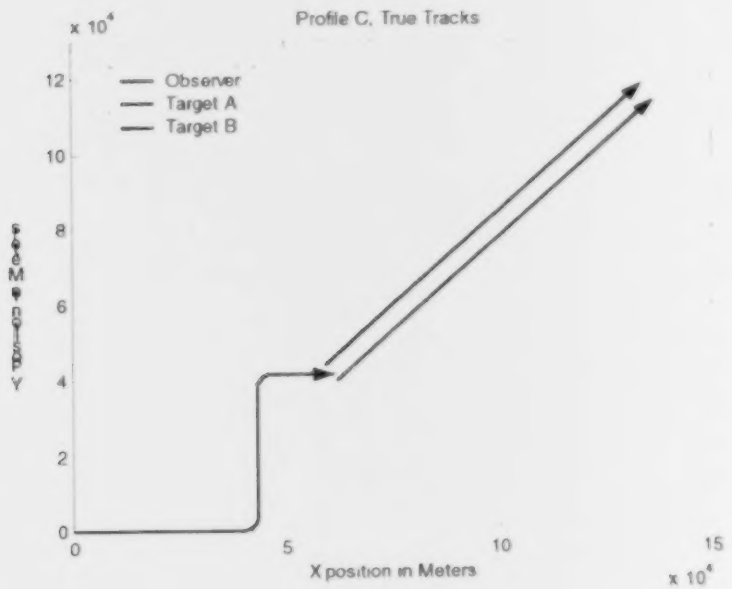

Figure 6. *True Tracks for Profile C*

Table 3. Initial kinematic parameters for profile C

PARAMETERS	OBSERVER	TARGET A	TARGET B
x(m)	0	60,000	60,000
y(m)	0	40,000	44,000

x (m/s)	200	150*cos(45°)	150*cos(45°)
y (m/s)	0	150*sin(45°)	150*sin(45°)

5. Tracking and Filtering

Target tracking is the processing of observations obtained from a target in order to maintain an estimate of its current state, which typically consists of:

1. Kinematic components such as position, velocity, acceleration, turn rate, etc...
2. Feature components such as radiated signal strength, Radar Cross Section (RCS), target classification, etc... ; and
3. Constant or slowly varying parameters such as aerodynamic parameters, etc... [4].

5.1 Standard Kalman Filtering

The Standard Kalman Filter (SKF) has found applications in a number of areas, such as tracking, state estimation, and parameter estimation. The SKF can be derived in a number of ways and all these techniques yield the same formulation when system and measurements models are linear and uncertainties are represented by zero-mean, white, Gaussian noise random variables. The SKF has a number of other advantages including:

- The Kalman gain sequence automatically adapts to changing detection histories including varying sampling period interval as well as missed detection.
- The Kalman filter provides a convenient measure of the estimation accuracy through the covariance matrix. This measure is actually required to perform gating accurately.

In this report, three filters are developed to evaluate the association techniques. The Converted Measurement Kalman Filter (CMKF) is chosen for the active sensor. Two different filters are used for the passive sensor. The first one uses an Extended Kalman Filter (EKF) with the Modified-Polar Coordinates (MPC) and the second filter uses an EKF with the Polar Coordinates. A brief description of these filters follows.

5.2 Converted Measurement Kalman Filter

In most target tracking applications, the target motion can be best modelled in the Cartesian coordinates. With active radar system the measurement of a target's position is typically reported in polar or spherical coordinates. If the motion equations are linear in the Cartesian coordinates and the observations are in the polar coordinates, one can obtain a polar-to-Cartesian linearization conversion. This conversion makes it possible to use the Kalman filter without the problems inherent to the Extended Kalman Filter (EKF). The resulting filter is called the Converted Measurement Kalman Filter (CMKF). The active sensor provides noisy measurements of the target(s) bearing (β), as well as the target(s) range (r). The state space model used for the active sensor measurement filter is represented by the following equations:

$$\mathbf{x}(k+1) = \Phi\mathbf{x}(k) + \mathbf{w}(k) + \mathbf{U}(k), \qquad \text{5- 1}$$

where $\mathbf{x}$, Φ, $\mathbf{w}$ $(\mathbf{0},\mathbf{Q})$, and $\mathbf{U}$, define, respectively, the state vector, the state transition matrix, the additive zero-mean, white Gaussian noise with known covariance Q, and the deterministic input such as the relative position change (acceleration) of the observer. The measurement vector $\mathbf{z}$ is modelled as

$$\mathbf{z}(k) = \mathbf{C}\mathbf{x}(k) + \mathbf{v}(k), \qquad \text{5- 2}$$

where $\mathbf{C}$ is the measurement matrix and $\mathbf{v}(k)$ is represented as

$$\mathbf{v}(k) = \begin{pmatrix} \cos(\beta) & -r\sin(\beta) \\ \sin(\beta) & r\cos(\beta) \end{pmatrix} \begin{pmatrix} \eta_r \\ \eta_\beta \end{pmatrix} \qquad \text{5- 3}$$

and η_r and η_β are zero-mean, white, Gaussian noise for the radar and ESM system, respectively. The measurement components of $\mathbf{z}(k)$ are represented by the familiar non-linear form of

$$\mathbf{z}(k) = \begin{bmatrix} r_m \\ \beta_m \end{bmatrix}. \qquad \text{5- 4}$$

where

$$r_m = \sqrt{x^2 + y^2} \text{ . and} \qquad \text{5- 5}$$

$$\beta_m = \tan^{-1}\left(\frac{x}{y}\right) \qquad \text{5- 6}$$

represent the measured range and measured bearing respectively.

In the CMKF, the polar measurements, the measured range and the measured bearing, are converted to the Cartesian coordinate system by the standard coordinate conversion as follows

$$x_m = r_m \cos(\beta_m) \text{ and } y_m = r_m \sin(\beta_m), \qquad 5\text{-}7$$

where x_m and y_m are the Cartesian measurements. The CMKF equations are summarized in Table 4.

The EKF is basically an extension of the linear SKF. The difference is that the EKF applies to non-linear measurement process and/or non-linear target dynamics cases. The basic idea is to linearize the equations with respect to each new estimate once it has been computed. As soon as a new state estimate is produced, a new and better reference state trajectory is incorporated into the estimation process [21]. So, the state update equation becomes

$$\hat{\mathbf{x}}(k \mid k) = \hat{\mathbf{x}}(k \mid k-1) + \mathbf{K}(k)[\mathbf{z}(k) - \mathrm{h}(\hat{\mathbf{x}}(k \mid k-1))] \qquad 5\text{-}8$$

where h($\hat{\mathbf{x}}(k|k\text{-}1)$) defines the non-linear measurement function. The gain is

$$\mathbf{K}(k) = \mathbf{P}(k \mid k-1)\mathbf{H}_x^T(k)[\mathbf{H}_x(k)\mathbf{P}(k \mid k-1)\mathbf{H}_x^T(k) + \mathbf{R}(k)]^{-1} \qquad 5\text{-}9$$

where $H_x(k)$ is the linearized measurement matrix expressed as

$$\mathbf{H}_x(k) = \left[\frac{\partial h}{\partial x}\right]_{x=\hat{\mathbf{x}}(k|k-1)} \qquad 5\text{-}10$$

5.3 Modified Polar Coordinates

A number of bearing-only Target Motion Analysis (TMA) algorithms have been proposed in the literature over the years [1,19,25], but this particular estimation problem does not have a simple solution. Non-linearity precludes the rigorous application of the SKF. While pseudo-linear formulations have been proposed in the literature, the resulting algorithms exhibit biased estimation problems. Moreover, since the bearing measurements are provided by only one sensor, the process remains unobservable until the observer manoeuvres [1,13,27]. This observability problem has been well documented in the literature [14,15,6]. The most common approach to this estimation problem is the EKF with Cartesian coordinates. The main advantage of this formulation is the minimisation of computational requirements achieved by the direct mapping of the physical system to the state equation [27]. However, new theoretical and experimental findings that have been published recently demonstrate

that the Cartesian approach is prone to premature covariance collapse prior to the first manoeuvre [1,27].

Table 4. Converted Measurement Kalman filter

Initial Estimates	$\hat{\mathbf{x}}(0\,|\,0)$ = Initial estimate for the state vector $\mathbf{P}(0\,|\,0)$ = Initial estimate for the state vector error covariance matrix
Predictions for the System State and for the Error Covariance P	$\hat{\mathbf{x}}(k\,|\,k-1) = \Phi\hat{\mathbf{x}}(k-1\,|\,k-1) + \mathbf{U}(k)$ $\mathbf{P}(k\,|\,k-1) = \Phi\mathbf{P}(k-1\,|\,k-1)\Phi^T + \mathbf{Q}(k)$
Gain	$\mathbf{K}(k) = \mathbf{P}(k\,|\,k-1)\mathbf{C}^T[\mathbf{C}\mathbf{P}(k\,|\,k-1)\mathbf{C}^T + \mathbf{R}(k)]^{-1}$ Where **R**(k) is the measurement error covariance matrix described as $\mathbf{R}(k) = \begin{bmatrix}\cos(\beta_m) & -r\sin(\beta_m)\\ \sin(\beta_m) & r\cos(\beta_m)\end{bmatrix}\begin{bmatrix}\sigma_r^2 & 0\\ 0 & \sigma_\beta^2\end{bmatrix}\begin{bmatrix}\cos(\beta_m) & -r\sin(\beta_m)\\ \sin(\beta_m) & r\cos(\beta_m)\end{bmatrix}^T$
Corrections for the System State and for the Error Covariance P	$\hat{\mathbf{x}}(k\,|\,k) = \hat{\mathbf{x}}(k\,|\,k-1) + \mathbf{K}(k)[\mathbf{z}(k) - \mathbf{C}\hat{\mathbf{x}}(k\,|\,k-1)]$ $\mathbf{P}(k\,|\,k) = [\mathbf{I} - \mathbf{K}(k)\mathbf{C}]\mathbf{P}(k\,|\,k-1)$ Where I represents the identity matrix

Aidala and Hammel proposed in [1] a different set of equations of the state and measurement formulated in Modified Polar Coordinates (MPC), while the algorithm

itself is configured as an EKF to solve the bearing only TMA problem. The state vector in MPC is

$$\mathbf{y} = \begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ y_4 \end{bmatrix} = \begin{bmatrix} \dot{\beta} \\ \dot{r}/r \\ \beta \\ 1/r \end{bmatrix} \qquad \text{5- 11}$$

where β represents the bearing rate, ($\dot{r} / r$) is the ratio of range rate and range. Also, it defines the measurement of the closeness of the observer to the target, which is called Inverse-Time-To-Go (ITTG). The MPC coordinate basis is well suited for Target Motion Analysis (TMA) as it automatically decouples the observable and unobservable components of the estimated state vector [1,13,27]. It is to be noted that the first three terms of the state vector are always observable while, the last term, (1 / *r*), is not observable until the observer performs a manoeuvre. An analysis performed in [14] reveals that the observer must manoeuvre to render the system observable and that certain manoeuvres are more appropriate than others for a given observer speed and profile. It is the need for a manoeuvre that distinguishes this bearing-only TMA from the more conventional localization (e.g. classical triangulation ranging) and tracking procedures [13].

It can be shown [1] that the dynamic state equation in MPC is nonlinear as follows:

$$\frac{d\mathbf{y}}{dt} = \begin{bmatrix} -2y_1y_2 + y_4(\mathbf{a}_x \cos(y_3) - \mathbf{a}_y \sin(y_3)) \\ y_1^2 - y_2^2 + y_4(\mathbf{a}_x \sin(y_3) - \mathbf{a}_y \cos(y_3)) \\ y_1 \\ -y_1y_4 \end{bmatrix} \qquad 5\text{-}12$$

where $\mathbf{a}_x$ and $\mathbf{a}_y$ are the Cartesian components of the relative acceleration between the observer and the target. If $\mathbf{a}_x = \mathbf{a}_y = 0$, then the first three components of the MPC are uncoupled with the fourth component. In the MPC, the dynamic state equation is nonlinear and the measurement equation is linear. The procedure to obtain the equation $\mathbf{y}(t) = \mathbf{f}(\mathbf{y}(t_0), \mathbf{a}, t, t_0)$ where $\mathbf{f}$ is a 4-dimensional vector whose components are nonlinear functions of the relative acceleration between the observer and the target, is the following:

1) Write the linear differential equation which describes the relative Cartesian motion of a target moving along a straight path with constant speed with respect to the observer;
2) Integrate the differential equation in (1) and derive a closed form expression for the target state vector in Cartesian coordinates;
3) Define the transformations equations between the two coordinates systems $\mathbf{x}(t) = \mathbf{f}_x(\mathbf{y}(t))$, $\mathbf{y}(t) = \mathbf{f}_y(\mathbf{x}(t))$;
4) Combine the equations of steps (2) and (3) to obtain $\mathbf{y}(t) = \mathbf{f}(\mathbf{y}(t_0), \mathbf{a}, t, t_0)$.

A more detailed derivation of the MPC equations may be found in [1,13]. Based on the MPC equations, the EKF is defined in Table 5 where $\hat{\mathbf{y}}(k \mid k-1)$, $\hat{\mathbf{y}}(k-1 \mid k-1)$, $\mathbf{P}(k/k)$ and $\mathbf{P}(k/k-1)$ are, respectively, the predicted state at time k given all the measurements up to the time k-1, the filtered state at time k given all the measurements up to time instant k, the covariance matrix of $\hat{\mathbf{y}}(k \mid k)$ and the covariance matrix of $\hat{\mathbf{y}}(k \mid k-1)$. $\mathbf{I}$ is the four-dimensional unit matrix. The nonlinear function $\mathbf{f}$ is linearized around the filtered value $\hat{\mathbf{y}}(k-1 \mid k-1)$ at time instant (k-1).

Table 5. Modified Polar Coordinates

Initial Estimates	$\hat{\mathbf{y}}(0\,|\,0)$ = Initial estimate of the state vector $\mathbf{P}(0\,|\,0)$ = Initial estimate of the state vector error covariance matrix
Predictions for the System State and for the Error Covariance P	$\hat{\mathbf{y}}(k\,|\,k-1)=\mathbf{f}[\hat{\mathbf{y}}(k-1\,|\,k-1);kT,(k-1)T]$ $\mathbf{A}_y(k\,|\,k-1)=\frac{\partial \mathbf{f}[\hat{\mathbf{y}}(k-1\,|\,k-1),kT,(k-1)T]}{\partial \hat{\mathbf{y}}(k-1\,|\,k-1)}$ $\mathbf{P}(k\,|\,k-1)=\mathbf{A}_y(k\,|\,k-1)\mathbf{P}(k-1\,|\,k-1)\mathbf{A}_y(k\,|\,k-1)^T$
Measurement Matrix	$\mathbf{C}=[0 \quad 0 \quad 1 \quad 0]$
Gain	$\mathbf{K}(k)=\mathbf{P}(k\,|\,k-1)\mathbf{C}^T[\mathbf{C}\mathbf{P}(k\,|\,k-1)\mathbf{C}^T+\sigma^2(k)]^{-1}$ Where $\sigma^2(k)$ is the variance of the angle measurement
Corrections for the System State and for the Error Covariance P	$\hat{\mathbf{y}}(k\,|\,k)=\hat{\mathbf{y}}(k\,|\,k-1)+\mathbf{K}(k)[z(k)-\mathbf{C}\hat{\mathbf{y}}(k\,|\,k-1)]$ $\mathbf{P}(k\,|\,k)=[\mathbf{I}-\mathbf{K}(k)\mathbf{C}]\mathbf{P}(k\,|\,k-1)$ Where I is the Identity matrix

5.4 Polar Coordinates

The second representation of the passive sensor is done in PC. In this coordinate basis, the filter simply smoothes the noisy bearing measurements. The state vector for the PC is as follow:

$$\mathbf{x}_p=\begin{bmatrix} x_{p1} \\ x_{p2} \\ x_{p3} \\ x_{p4} \end{bmatrix}=\begin{bmatrix} \dot{\beta} \\ \dot{r} \\ \beta \\ r \end{bmatrix} \qquad \text{5- 13}$$

The non-linear differential equations describing the evolution of the target course in these coordinate system are

$$\frac{d\mathbf{x}_p}{dt} = \begin{bmatrix} -2x_{p2}x_{p1} \Big/ x_{p4} + 1 \Big/ x_{p4} (a_x \cos(x_{p3}) - a_y \sin(x_{p3})) \\ x_{p1}^2 x_{p4} + (\mathbf{a}_x \sin(x_{p3}) - \mathbf{a}_y \cos(x_{p3})) \\ x_{p1} \\ x_{p2} \end{bmatrix} \qquad 5\text{-}14$$

Based on the PC equations. the EKF is defined in Table 6.

Table 6. *Polar Coordinates*

Initial Estimates	$\hat{\mathbf{x}}_p(0\mid 0)$ = Initial estimate of the state vector $\mathbf{P}(0\mid 0)$ = Initial estimate of the state vector error covariance matrix
Predictions for the System State and for the Error Covariance P	$\hat{\mathbf{x}}_p(k\mid k-1) = \mathbf{f}[\hat{\mathbf{x}}_p(k-1\mid k-1); kT, (k-1)T]$ $\mathbf{A}_v(k\mid k-1) = \dfrac{\partial \mathbf{f}[\hat{\mathbf{x}}_p(k-1\mid k-1), kT, (k-1)T]}{\partial \hat{\mathbf{x}}_p(k-1\mid k-1)}$ $\mathbf{P}(k\mid k-1) = \mathbf{A}_v(k\mid k-1)\mathbf{P}(k-1\mid k-1)\mathbf{A}_v(k\mid k-1)^T$
Measurement Matrix	$\mathbf{C} = [0 \quad 0 \quad 1 \quad 0]$
Gain	$\mathbf{K}(k) = \mathbf{P}(k\mid k-1)\mathbf{C}^T[\mathbf{C}\mathbf{P}(k\mid k-1)\mathbf{C}^T + \sigma^2(k)]^{-1}$ Where $\sigma^2(k)$ is the variance of the measurement $z(k)$
Corrections for the System State and for the Error Covariance P	$\hat{\mathbf{x}}_p(k\mid k) = \hat{\mathbf{x}}_p(k\mid k-1) + \mathbf{K}(k)[z(k) - \mathbf{C}\hat{\mathbf{x}}_p(k\mid k-1)]$ $\mathbf{P}(k\mid k) = [\mathbf{I} - \mathbf{K}(k)\mathbf{C}]\mathbf{P}(k\mid k-1)$ Where I is the Identity matrix

5.5 Cartesian to MPC transformation

This section describes the transformation of the Cartesian estimates into MPC bearing and ITTG estimates. Given that

$$x = r\sin(\beta) \text{ and } y = r\cos(\beta),$$

and that

$$\beta = \tan^{-1}\left(\frac{x}{y}\right),$$

$$\frac{1}{r} = \frac{1}{\sqrt{x^2 + y^2}}.$$

From this it follows that

$$\dot{x} = \dot{r}\sin(\beta) + r\dot{\beta}\cos(\beta) \qquad \text{5- 15}$$

$$\dot{y} = \dot{r}\cos(\beta) - r\dot{\beta}\sin(\beta) \qquad \text{5- 16}$$

Multiplying (5-13) by $\sin(\beta)$ and (5-14) by $\cos(\beta)$, and subtracting the result obtained from each manipulation, gives the following expression

$$\dot{x}\sin(\beta) + \dot{y}\cos(\beta) = \dot{r} \qquad \text{5- 17}$$

Replacing $\sin(\beta)$ and $\cos(\beta)$ by their Cartesian component and performing a few manipulations, we obtain the following equation

$$\left(\frac{\dot{r}}{r}\right) = \frac{(\dot{x}x + \dot{y}y)}{(x^2 + y^2)} \qquad \text{5- 18}$$

The covariance matrix for β_{radar} and $\dot{G}_{radar}$ is given by $\mathbf{U}(\hat{\mathbf{x}}_{radar})\,\mathbf{P}_{radar}\,\mathbf{U}^T(\hat{\mathbf{x}}_{radar})$, where $\mathbf{P}_{radar}$ is the solution to the Riccati equation for the active filter and

$$\mathbf{U}(\mathbf{x}) = \left[\frac{\partial u_i}{\partial x_j}\right]_{\hat{\mathbf{x}}} \qquad \text{5- 19}$$

Since we have

$$G_{radar} = u_1(x) = \frac{(\dot{x}x - \dot{y}y)}{(x^2 + y^2)} \qquad \text{5- 20}$$

$$\beta_{radar} = u_2(x) = \tan^{-1}\left(\frac{x}{y}\right) \qquad \text{5- 21}$$

$$\mathbf{U}(\mathbf{x}) = \begin{bmatrix} \dfrac{(x^2+y^2)\dot{x} - (\dot{x}x + \dot{y}y)2x}{(x^2+y^2)^2} & \dfrac{(x^2+y^2)x}{(x^2+y^2)^2} & \dfrac{(x^2+y^2)\dot{y} - (\dot{x}x + \dot{y}y)2y}{(x^2+y^2)^2} & \dfrac{(x^2+y^2)y}{(x^2+y^2)^2} \\ \dfrac{1}{1+\left(\dfrac{x}{y}\right)^2}\left(\dfrac{1}{y}\right) & 0 & \dfrac{1}{1+\left(\dfrac{x}{y}\right)^2}\left(\dfrac{-x}{y^2}\right) & 0 \end{bmatrix}$$

5- 22

6. Track to track association

6.1 Association logic

The association logic used to evaluate the performance of the track-to-track association techniques is a classical association algorithm described as follows. Under the same assumptions, the association logic should decide whether the measurements provided by the active and passive systems are from the same target (H_0) or if they belong to different targets (H_1). Assuming the two target tracks are $\hat{\mathbf{x}}_{radar}$ and $\hat{\mathbf{x}}_{esm}$ for the active and passive cases, respectively, the association logic test, referred to as the statistical distance test statistic is

$$(\hat{\mathbf{x}}_{radar} - \hat{\mathbf{x}}_{esm})(\mathbf{P}^{ij})^{-1}(\hat{\mathbf{x}}_{radar} - \hat{\mathbf{x}}_{esm})^T \leq \lambda \qquad \text{6-1}$$

where

$$\mathbf{P}^{ij} = \mathbf{P}_a^i + \mathbf{P}_p^j - \mathbf{P}^c - (\mathbf{P}^c)^T,$$

and $\mathbf{P}_a^i$ and $\mathbf{P}_p^j$ are the covariance matrices, solutions of the Riccati equations in the Kalman filters [29] used for the active and passive cases, respectively, assuming the process noise is Gaussian and independent for each filter. In general, the cross-covariance term $\mathbf{P}^c$ will not be zero as the state estimate errors will be correlated if the trajectories are from the same target due to the common process noise in each filter. In this case, the cross-covariance is assumed to be zero. The expression in equation (6-1) represents a χ^2 distribution with n degrees of freedom where n is the dimension of the state vectors under evaluation.

This test is designed to select between two hypotheses, H_0: the tracks are from the same target, and H_1: the tracks are from different targets. Here we introduce a variation of the previously described statistical distance test statistic in equation (6-1), where we allow a window (d) of measurements to be used to compute the test statistic. This method allows us to go back in time and use measurements observed by previous scan (back scanning). The equation then becomes

$$\sum_{r=0}^{d-1}\left[(\hat{\mathbf{x}}_{radar}-\hat{\mathbf{x}}_{esm})(\mathbf{P}^{ij})^{-1}(\hat{\mathbf{x}}_{radar}-\hat{\mathbf{x}}_{esm})^{T}\right]_{k-r)} \le \lambda \qquad 6\text{-}2$$

where k is the time instant and r is the delay. The distribution of this test is approximately χ^2 with dn degrees of freedom [11].

6.2 Association techniques

Five track-to-track association approaches are described here. The first two techniques are commonly used methods while the three remaining were introduced in [11]. Two of the newer association techniques make use of the ITTG ($G = \dot{r} / r$) element available from the MPC filter. The five association techniques are:

1. Method 1 compares the bearing estimates from the active filter (β_{radar}) with the bearing estimates from the PC filter ($\beta 1_{esm}$);
2. Method 2 compares β_{radar} with the bearing estimates from the MPC filter ($\beta 2_{esm}$);
3. Method 3 compares the bearing and the ITTG estimates from the active filter [β_{radar}, $\hat{G}_{radar}$] with the bearing and ITTG estimates from the MPC filter [$\beta 2_{esm}$, $\hat{G}2_{esm}$];
4. Method 4 compares β_{radar}, with the measured bearing (β_m) from the ESM system; and
5. Method 5 compares [β_{radar}, $\hat{G}_{radar}$] with β_m and $\hat{G}2_{esm}$.

The following figure illustrates the model of these five track-to-track association techniques with respect to the different sensors, filters, and measurements.

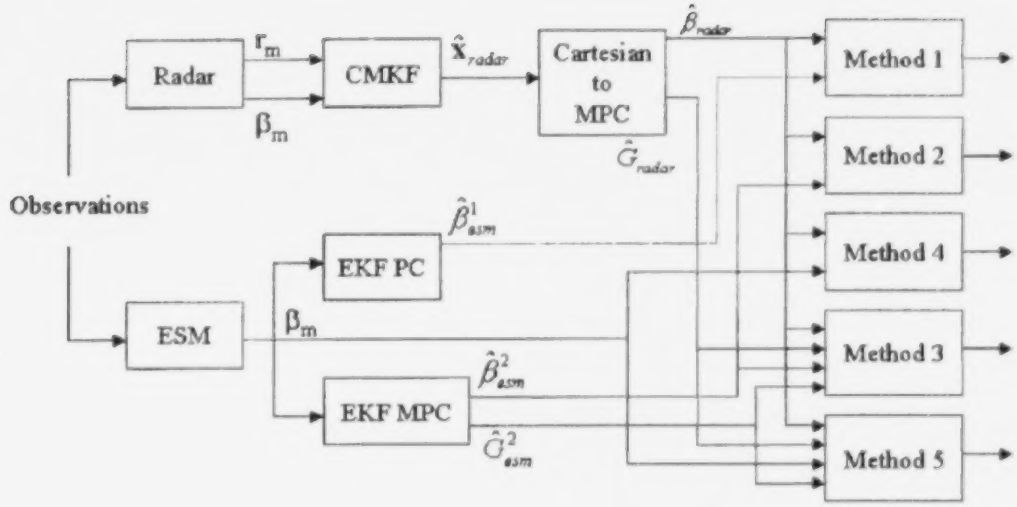

Figure 7. Track to track association techniques [11]

6.3 association evaluation

6.3.1 Simulation Set-up

A number of Monte Carlo simulations have been carried out for the three defined profiles to determine the performance of the five different association techniques. The sampling period (T) is chosen to be 4 seconds. One hundred runs were performed for every case under consideration. The measurement noises were set as follows:

a) Range noise (σ_r) = 10 meters;

b) Bearing noise (σ_{β_1}) for the active sensor = 1 degree; and

c) Bearing noise (σ_{β_2}) for the passive sensor = 3 degrees.

Each of the five association methods have been examined for all possible window sizes (d = 1 to 3). The performance of these techniques is compared in terms of Probability of False Association (P_{fa}) and Probability of Correct (P_c) association.

6.3.2 Probability of Correct Association

For Profile A, the P_c has been computed for the five association techniques. This test evaluates how often the methods correctly associate the radar and ESM tracks when they are both from the same target. As shown in Figure 8, the performance of the first association approach is limited. This poor performance is attributed to the PC model, which is a not a good choice for extrapolating target position between sensor updates. This is particularly true at shorter ranges, where the pseudo-accelerations created by constant speed/constant course targets, introduce very large errors in polar tracking [5,18], which is the case of Profile A, where the targets are moving toward the observer causing the range to decrease rapidly.

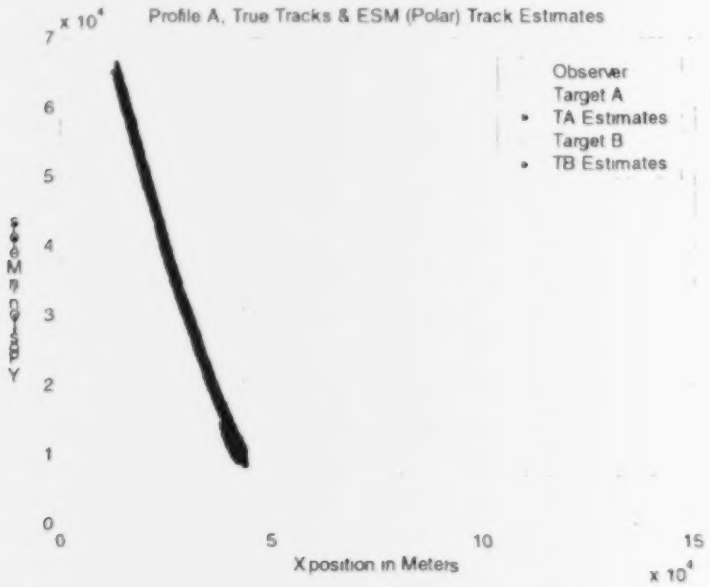

Figure 8. Filter track estimates in polar coordinates

The statistical distance test statistic in equation (6-1) has been computed and compared against the appropriate 95% point from χ^2 table. Figure 9 presents the results when the window length d = 1.

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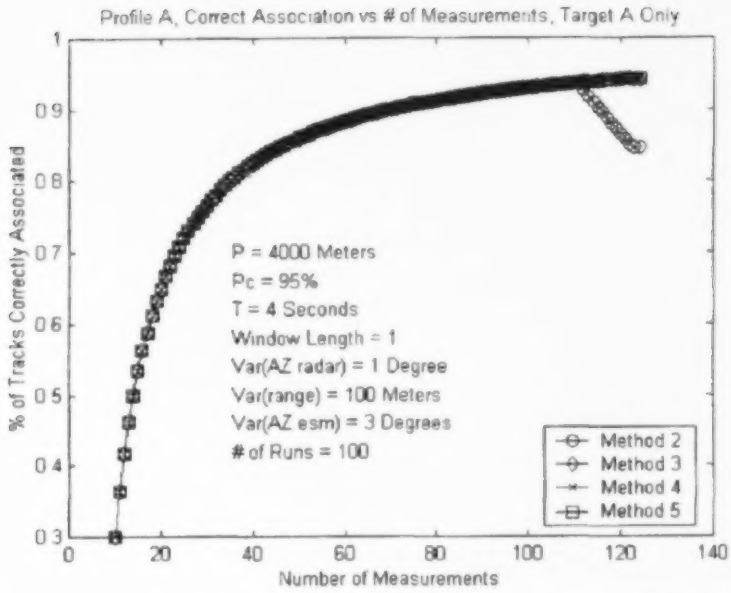
Profile A, Correct Association vs # of Measurements, Target A Only
% of Tracks Correctly Associated
Number of Measurements
P = 4000 Meters
Pc = 95%
T = 4 Seconds
Window Length = 1
Var(AZ radar) = 1 Degree
Var(range) = 100 Meters
Var(AZ esm) = 3 Degrees
# of Runs = 100
Method 2
Method 3
Method 4
Method 5

Figure 9. *Profile A, correct association vs number of measurements*

From this figure, it is clear that all the methods provide basically the same P_c for Profile A as the number of measurement increases. There is, however, a slight decrease in the P_c for Method 2. This result can be explained by a decrease in bearing rate for the passive system after the manoeuvre that causes an increase in the error for the $\beta 2_{esm}$ in Method 2. The other methods are less affected by the turn.

When the window length d, which allows for the use of measurements collected on previous scans, is increased, Methods 3 and 5 experience a slight reduction in performance. This is explained by the fact that there is an accumulation in ITTG error, which varies greatly before the first turn. So, the averaging performed when adding samples has actual adverse effect in this case.

The P_c has been evaluated for the five association techniques with Profile B. The statistical distance test statistic has been computed and compared against the appropriate 95% point from χ^2 table. Figure 10 shows the results when $d = 1$.

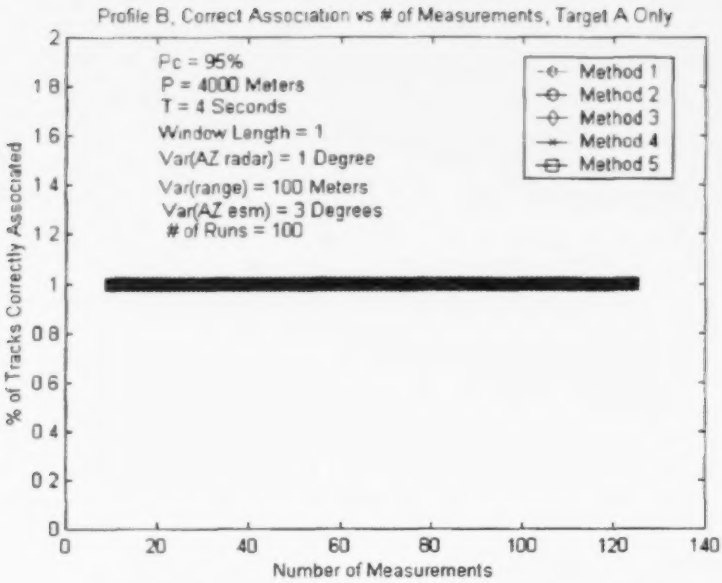

Figure 10. *Profile B, correct association vs number of measurements*

Examination of Figure 10 reveals that the five techniques performed very well. This result is explained by a reduction in bearing error in both ESM filters provided by Profile B. Hammel in [1] performed a series of tests on observer courses and found that equally weighted position and velocity errors are minimized by geometries that provide the best compromise between increased bearing rate and reduced relative range. For systems without process noise and low measurement noise, this requirement manifests itself in an observer profile, which periodically intersects the target's LOS. Profile B is a good example of such a situation.

The performance of the association techniques remained unchanged with an increase in window size except for Methods 3 and 5, which experience a small reduction in P_c. This is caused by a slight increase in the error between the estimates used to perform the test as well as the accumulation of errors from previous scans, which are always worse.

Finally, the P_c for the five association techniques is computed using Profile C. The statistical distance test statistic has been computed and compared against the appropriate 95% point from χ^2 table. Figure 11 shows the results when the window length $d = 1$.

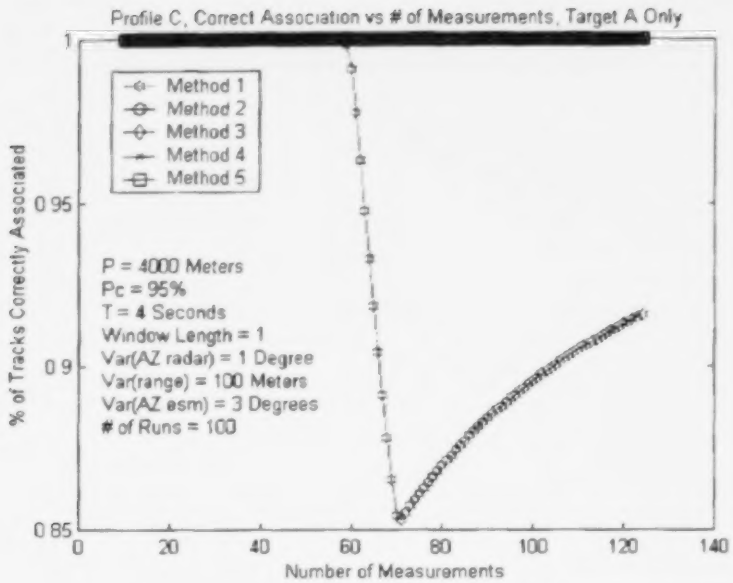

Figure 11. *Profile B, correct association vs. number of measurements*

These results are very similar to the Profile B, except that Method 1 experiences a reduction in performance after the first turn. This is caused by a short-term (about 60 seconds) sharp increase in the bearing error for the PC filter after the turn. An increase in window length d produces the same phenomena as previously explained for Profile B, where the accumulation of errors for the ITTG estimates results in a reduction in performance for Methods 3 and 5.

6.3.3 Probability of false association

In addition to correctly associating tracks from the same target, these association techniques should be able to determine when tracks are from different targets. To calculate the P_{fa}, a second target trajectory, which is parallel to that of Target A, was generated. Assuming a distance of 4,000 meters between the targets, the radar tracks Target A while the ESM system tracks Target B. The statistical distance test statistic has been computed and compared against the appropriate 95% point from χ^2 table. Figure 12 presents the results when $d = 1$.

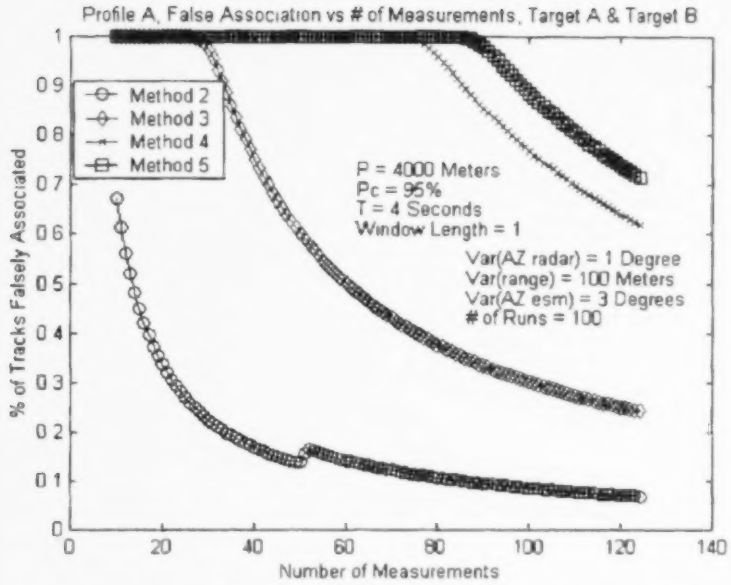

Figure 12. *Profile A, false association vs. number of measurements*

It is evident from Figure 12 that Methods 2 and 3 outperformed Methods 4 and 5, which use noisy measurements. This is caused by a higher measured bearing (β_m) error in the case of Method 4 and 5 compared to the bearing estimate ($\beta 2_{esm}$) error produced by Method 2 and 3. Increasing d results in Method 5 becoming more reliable than Method 3 while Method 2 remains the best option.

Next, the P_{fa} has been evaluated for the five association techniques with Profile B and the statistical distance test statistic has been computed and compared against the appropriate 95% point from χ^2 table. Figure 13 presents the results when $d = 1$.

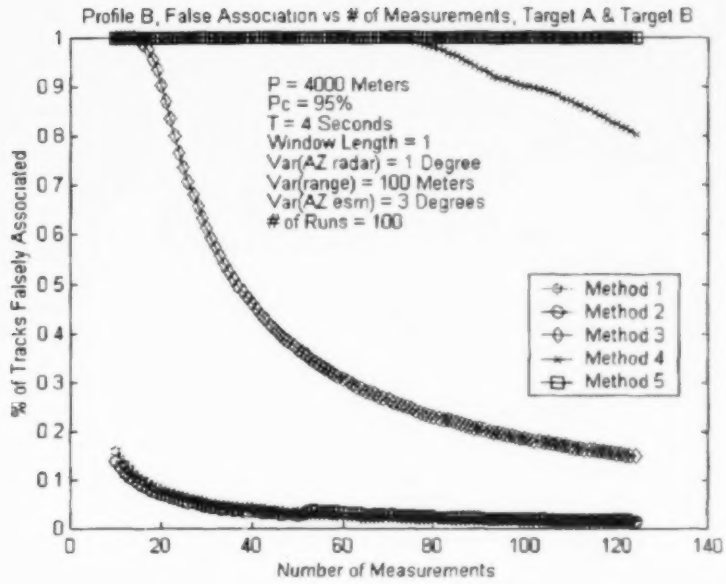

Figure 13. *Profile B, false association vs number of measurements*

Figure 13 illustrates that Method 1, 2 and 3 outperform Method 4 and 5, which use noisy measurements. This result is attributed mainly to a bigger bearing error and a higher $(P^{ij})^{-1}$ contribution (Figure 14) to the statistical distance causing a higher false association rate in the case of Methods 4 and 5.

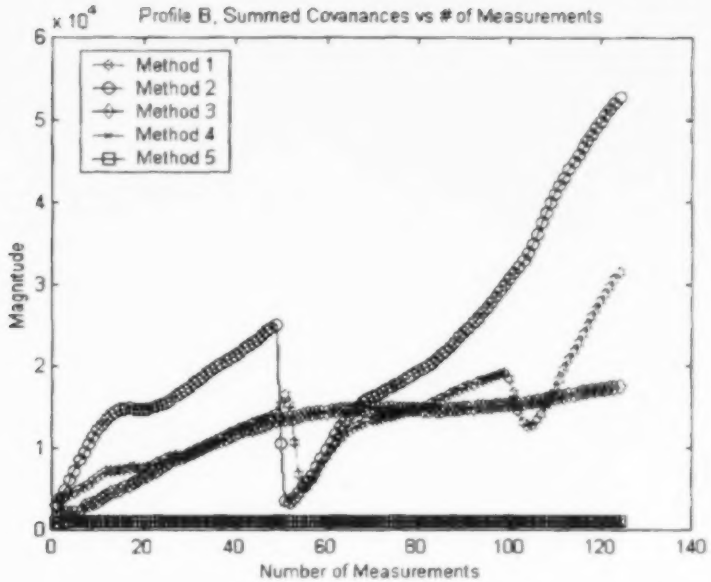

Figure 14. *Profile B, summed covariances*

Finally, P_{fa} has been evaluated for the five different association techniques with Profile C. Figure 15 presents the results when the window length $d = 1$. It is clear that the results are very similar to those of Profile B. Methods 1, 2 and 3 outperform Methods 4 and 5 (Figure 15). Unlike results in Figure 13, Method 1 is clearly performing better than Method 2 for this profile. While the bearing error remains higher for Method 1, the contribution of the term $(P^{ij})^{-1}$ is lower than that in Method 2.

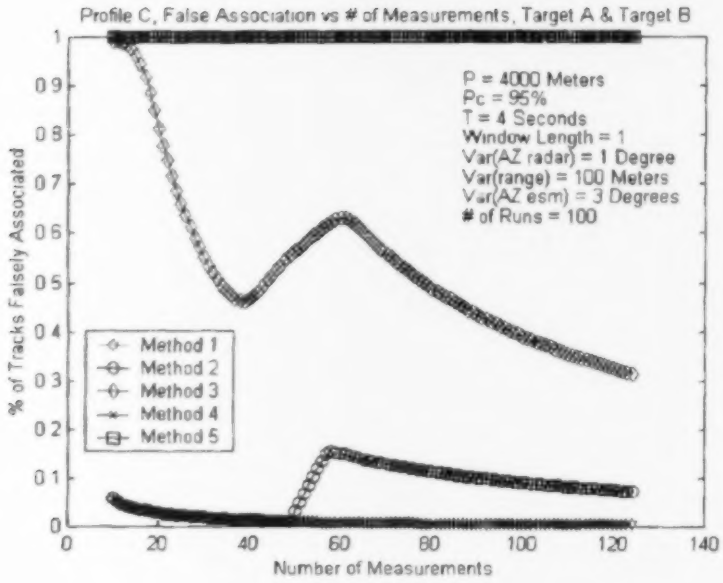

Figure 15. *Profile C, false association vs. number of measurements*

6.3.4 P_{fa} vs Separation Between the Targets

To further evaluate the performance of the five track-to-track association techniques in terms of P_{fa}, the curves showing the percentage of false association versus the distance separating the two targets is shown in Figures 16 to 18 for each profile. These plots allow us to determine if the approaches can distinguish between two closely spaced targets. Figure 16 presents the results for Profile A when $d = 1$.

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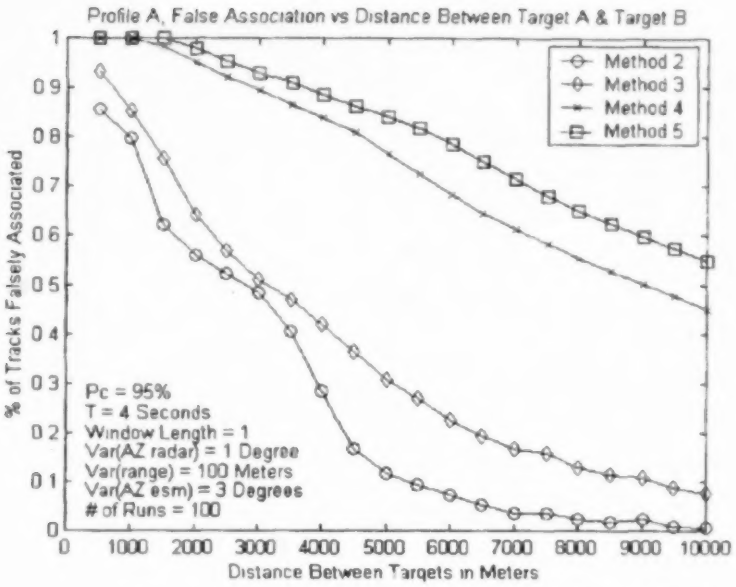

Figure 16. *Profile A, false association vs distance between targets*

Figures 17 and 18 present the results for Profile B and C, respectively, when the window length $d = 1$.

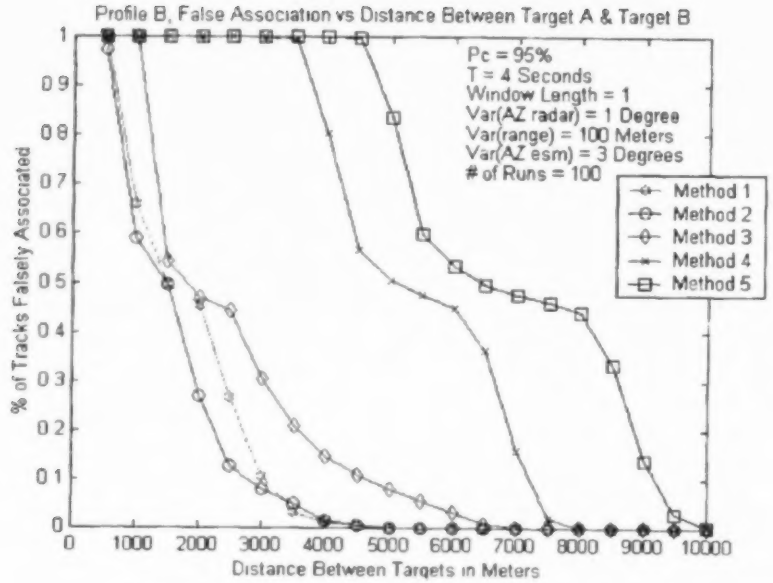
Profile B, False Association vs Distance Between Target A & Target B
Pc = 95%
T = 4 Seconds
Window Length = 1
Var(AZ radar) = 1 Degree
Var(range) = 100 Meters
Var(AZ esm) = 3 Degrees
# of Runs = 100
Method 1
Method 2
Method 3
Method 4
Method 5
% of Tracks Falsely Associated
Distance Between Targets in Meters

Figure 17. *Profile B, false association vs distance between targets*

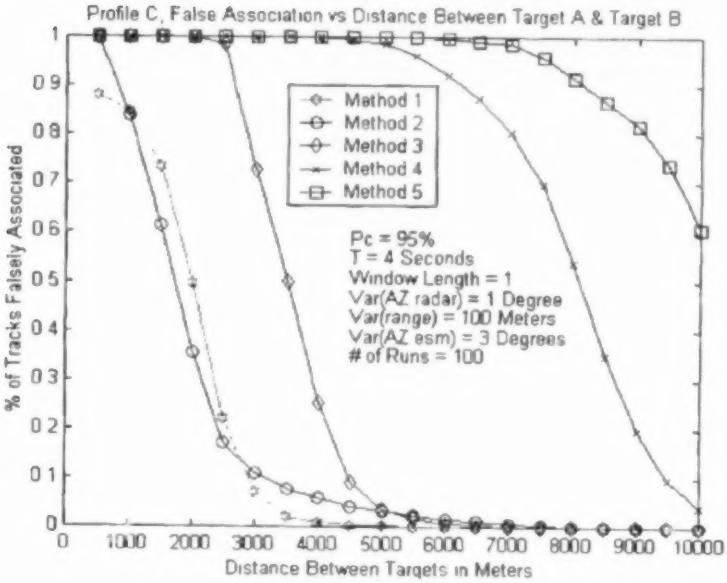
Profile C, False Association vs Distance Between Target A & Target B
Method 1
Method 2
Method 3
Method 4
Method 5
Pc = 95%
T = 4 Seconds
Window Length = 1
Var(AZ radar) = 1 Degree
Var(range) = 100 Meters
Var(AZ esm) = 3 Degrees
# of Runs = 100
% of Tracks Falsely Associated
Distance Between Targets in Meters

Figure 18. *Profile C, false association vs. distance between targets*

The results presented in Figures 16 to 18 demonstrate that Methods 1, 2, and 3, which use bearing estimates, are better than Methods 4 and 5, which use noisy bearing measurements in distinguishing between two targets Moreover, the performance of each method improves, as expected, as the distance between the targets increases. The results of this study do not demonstrate that the methods (Methods 2 and 3) using the MPC filter are better than Method 1. The dissimilar results are attributed to the type of profiles utilized in this study.

7. Conclusion

In this report, we explored the problem of associating ESM tracks with one or more possible radar tracks derived in different coordinate systems. Simulation results show that the choice of the coordinate system is a complex issue, which depends not only on the sensors but also on the scenario. One important outcome of this study is that Methods 1,2 and 3, which use bearing estimates to compute the track-to-track association, are capable of correctly associating two closely spaced targets, while Methods 4 and 5, which rely on measured ESM bearing for the association between tracks, are not reliable. The study also demonstrates that association Method 1, using the PC based estimates, and Method 2, using the MPC based estimates, have comparable performances.

8. Acknowledgement

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In this report, we present different approaches for the association of tracks for airborne sensors The proposed approaches explore the effects of the choice of coordinate systems on the tracking filters and the association process The performance of the association techniques is analyzed in terms of the probability of correct association (Pc) and the probability of false association (Pfa) This practical aspect of the multi-target multi-sensor tracking problem is presented for the association of radar tracks to ESM tracks in different scenarios.

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